Adaptive Neural Network Control for Constrained Robot Manipulators

Gang Wang[1], Tairen Sun[1], Yongping Pan[2], and Haoyong Yu[2](✉)

[1] Jiangsu University, Zhenjiang 212013, China
973196357@qq.com, suntren@gmail.com
[2] National University of Singapore, Singapore 117583, Singapore
{biepany,bieyhy}@nus.edu.sg

Abstract. This paper presents an adaptive neural network (NN) control strategy for robot manipulators with uncertainties and constraints. Position, velocity and control input constraints are considered and tackled by introducing barrier Lyapunov functions in the backstepping procedure. The system uncertainties are estimated and compensated by a locally weighted online NN. The boundedness of the closed-loop control system and the feasibility of the proposed control law are demonstrated by theoretical analysis. The effectiveness of the proposed control strategy has been verified by simulation results on a robot manipulator.

Keywords: Adaptive control · Backstepping · Neural network · System constraint · Barrier Lyapunov function · Robot manipulator

1 Introduction

Control of robot manipulators has gained more and more attention for its applications in industries, agricultures, and teleoperated surgeries. The difficulties in control of robot manipulators mainly include uncertainties and constraints in the position, velocity, and control input. On the one hand, uncertainties always exist in robot manipulator models due to modeling errors and disturbances. On the other hand, control input constraints always exist due to limited control powers, and motion constraints (e.g. position constraints and velocity constraints) are needed to avoid collision or injury to human beings, especially in human-robot interaction. Therefore, the control design for robot manipulators with uncertainties and constraints deserves more research.

Many robust control strategies have been developed for robot manipulators, including sliding mode control [1–3], neural network (NN) control [3–8], fuzzy control [9,10], adaptive control [11], etc. However, sliding mode control usually suffers from chattering and the need of high-frequency bandwidth, adaptive control usually only handles structured uncertainties, and fuzzy control highly depends on the experiences of control engineers. Compared with other control approaches, NN control has its own advantages. NNs can approximate both structured and unstructured uncertainties due to their inherent function

F. Cong et al. (Eds.): ISNN 2017, Part II, LNCS 10262, pp. 118–127, 2017.
DOI: 10.1007/978-3-319-59081-3_15

approximation abilities. The use of NNs estimators in control is possible to obtain desired control performances without high control gains.

Since constraints in robot manipulators need to be considered and ignoring constraints may deteriorate the control performance, some results have been obtained on control of constrained robot manipulators. Set-point regulation control and tracking control laws were designed in [12] and [13] for robot manipulators with velocity constraints, respectively. Quadratic programming-based kinematic control was developed in [14,15] for velocity constrained redundant manipulators. Joint position constraints were considered and optimal control was designed based on adaptive dynamic programming in [16]. Recently, adaptive control was developed for robot manipulators where output or state constraints are tackled by bounding barrier Lyapunov functions (BLFs) in [17,18]. Based on the above analysis, one can see that only position or joint velocity constraints are considered in existing robot manipulators control approaches.

In this paper, an adaptive NN control law is proposed for robot manipulators with uncertainties and constraints, including position, velocity and control constraints. The uncertainties are approximated by locally weighted adaptive NNs and compensated by the NN estimator in the control law. In locally weighted NNs, estimators composed of independently adjusted local models are used to reach the desired approximation accuracy. Thus, fewer neurons are needed to approximate smooth functions in the desired accuracy compared with other NNs. The system constraints are tackled by using BLFs in the backstepping control [19,20] design for robot manipulators, which extends BLFs-based control for output and state constrained systems [17] to state and control constrained systems. It is demonstrated that uniform boundedness of all closed-loop signals is obtained while the constraints are not violated in theory.

2 Problem Statement

Consider a n-link robot manipulator with the following dynamics:

$$M(q)\ddot{q} + V_m(q,\dot{q})\dot{q} + F\dot{q} + G(q) = \tau \tag{1}$$

where $q = q_1 = [q_{11}, q_{12}, \cdots, q_{1n}]^T \in R^n$ is a joint angle, $q_2 = \dot{q}_1 = [q_{21}, q_{22}, \cdots, q_{2n}]^T$ is a joint velocity, $M(q) \in R^{n\times n}$ is an inertia matrix, $V_m(q,\dot{q}) \in R^{n\times n}$ is a centripetal and Coriolis matrix, $F\dot{q} \in R^n$ denotes a viscous friction torque, $G(q) \in R^n$ denotes a gravitation torque, and $\tau \in R^n$ denotes a control torque.

Assumption 1. $M(q)$ satisfies the following inequalities:

$$m_1||x||^2 \le x^T M(q)x \le m_2||x||^2,\ x \in R^n \tag{2}$$

where m_1, $m_2 \in R$ are positive constants.

Assumption 2. The uncertain function $f(q,\dot{q}) = M^{-1}(q)[V_m(q,\dot{q})\dot{q} + F\dot{q} + G(q)]$ is continuous.

Assumption 3. The reference trajectory is described as $y_d(t) = [y_{d1}, y_{d2}, \cdots, y_{dn}]^T \in R^n$ and satisfies $|y_{di}| \le A_i$ and $|\dot{y}_{di}| \le Y_i, i = 1, \cdots, n$.

The objective is to design an adaptive NN control law for the system (refeq1) to track desired trajectory $q_d(t)$ and to satisfy the following constraints:

$$|q_{1i}| \le b_{1i},\ |q_{2i}| \le b_{2i},\ |\tau_i| \le \tau_{di},\ i = 1, 2, \cdots, n. \tag{3}$$

3 BLF-Based Neural Control

3.1 Control Design

Let $e_1 = [e_{11}, e_{12}, e_{13}]^T = q_1 - y_d$ be a tracking error. Consider BLFs as follows:

$$V_1 = \frac{1}{2}\sum_{i=1}^{n} \frac{k_{1i}^2}{k_{1i}^2 - e_{1i}^2} \tag{4}$$

with k_{1i} to k_{1n} being positive design parameters. The time derivative of V_1 is

$$\dot{V}_1 = \sum_{i=1}^{n} \frac{e_{1i}}{k_{1i}^2 - e_{1i}^2}(q_{2i} - \dot{y}_{di}). \tag{5}$$

Design the following virtual control input:

$$\alpha_{1i} = \dot{y}_{di} - \lambda_{1i} e_{1i},\ i = 1, 2, \cdot, n \tag{6}$$

with $\lambda_{1i}, i = 1, 2, \cdots, n$ being positive parameters.

Let $e_2 = [e_{21}, \cdots, e_{2n}]^T = [q_{21} - \alpha_{11}, \cdots, q_{2n} - \alpha_{1n}]^T$. Then, one has

$$\dot{V}_1 = -\sum_{i=1}^{n} \lambda_{1i} \frac{e_{1i}^2}{k_{1i}^2 - e_{1i}^2} + \sum_{i=1}^{n} \frac{e_{1i} e_{2i}}{k_{1i}^2 - e_{1i}^2}. \tag{7}$$

Consider the following BLFs:

$$V_2 = V_1 + \Lambda_1, \tag{8}$$

$$\Lambda_1 = \sum_{i=1}^{n} \frac{1}{2} \log \frac{k_{2i}^2}{k_{2i}^2 - e_{2i}^2} \tag{9}$$

with k_{2i} to k_{2n} being positive design parameters. The time derivative of Λ_1 is

$$\begin{aligned} \dot{\Lambda}_1 &= \sum_{i=1}^{n} \frac{e_{2i}}{k_{2i}^2 - e_{2i}^2}(\dot{q}_{2i} - \dot{\alpha}_{1i}) \\ &= \xi^T (f(q_1, q_2) + M^{-1}(q_1)\tau - [\dot{\alpha}_{11}, \cdots, \dot{\alpha}_{1n}]^T) \end{aligned} \tag{10}$$

where

$$\xi = \left[\frac{e_{21}}{k_{21}^2 - e_{21}^2}, \cdots, \frac{e_{2n}}{k_{2n}^2 - e_{2n}^2}\right]^T. \tag{11}$$

Design the reference signal τ_r for τ as

$$\tau_r = [\tau_{r1}, \cdots, \tau_{rn}]^T = M(q_1)(-\lambda_2 e_2 - \hat{f}(q_1, q_2) - s) \quad (12)$$

where λ_2 is a positive design parameter, $\hat{f}(q_1, q_2)$ is an estimate of $f(q_1, q_2)$, and

$$s = \frac{1}{2}\xi - [\dot{\alpha}_{11}, \cdots, \dot{\alpha}_{1n}]^T + [(k_{21}^2 - e_{21}^2)e_{11}/(k_{11}^2 - e_{11}^2), \cdots, (k_{2n}^2 - e_{2n}^2)e_{1n}/(k_{1n}^2 - e_{1n}^2)]^T. \quad (13)$$

Define $e_3 = [e_{31}, \cdots, e_{3n}]^T = \tau - \tau_r$. From (7)–(13), one obtains

$$\dot{V}_2 = -\sum_{i=1}^{n} \lambda_{1i} \frac{e_{1i}^2}{k_{1i}^2 - e_{1i}^2} - \sum_{i=1}^{n} \lambda_2 \frac{e_{2i}^2}{k_{2i}^2 - e_{2i}^2} + \xi^T(\tilde{f} + M^{-1}e_3) - \frac{1}{2}\xi^T\xi \quad (14)$$

Consider the following BLF:

$$V_3 = V_2 + \Lambda_2, \quad (15)$$

$$\Lambda_2 = \sum_{i=1}^{n} \frac{1}{2} \log \frac{k_{3i}^2}{k_{3i}^2 - e_{3i}^2} \quad (16)$$

with k_{3i} to k_{3i} being positive design parameters. Time derivative of Λ_2 is

$$\dot{\Lambda}_2 = \eta^T(\dot{\tau} - \dot{\tau}_r) \quad (17)$$

where

$$\eta = [\frac{e_{31}}{k_{31}^2 - e_{31}^2}, \cdots, \frac{e_{3n}}{k_{3n}^2 - e_{3n}^2}]^T \quad (18)$$

If the control law for the robot manipulator (1) is designed as follows:

$$\tau = -\lambda_3 \int_0^t e_3(\sigma)d\sigma - \int_0^t [\mathrm{diag}\{k_{3i}^2 - e_{3i}^2\}M^{-1}(q_1)\xi](\sigma)d\sigma + \tau_r(t) \quad (19)$$

where λ_3 is a positive parameter, then one gets

$$\dot{V}_3 = -\sum_{i=1}^{n} \lambda_{1i} \frac{e_{1i}^2}{k_{1i}^2 - e_{1i}^2} - \sum_{i=1}^{n} \lambda_2 \frac{e_{2i}^2}{k_{2i}^2 - e_{2i}^2} - \sum_{i=1}^{n} \lambda_3 \frac{e_{3i}^2}{k_{3i}^2 - e_{3i}^2} + \xi^T\tilde{f} - \frac{1}{2}\xi^T\xi. \quad (20)$$

3.2 Locally Weighted Online NN Approximation

Let $X = [X_1, \cdots, X_{2n}]^T = [q_1^T, q_2^T]^T$ and $D = \{X : |X_i| \leq b_{1i}, |X_{n+i}| \leq b_{2i}, i = 1, \cdots, n\}$. The locally weighted NN approximation of $f(X)$ is described by

$$\hat{f}(X) = \frac{\sum_{k=1}^{N} w_k(X)\hat{f}_k(X)}{\sum_{k=1}^{N} w_k(X)} \quad (21)$$

where $w_k(X), k = 1, \cdots, N$ as weighted functions, and the local estimator $\hat{f}_k(X)$ is described as follows:

$$\hat{f}_k(X) = \theta_k^T \phi_k(X),\ \ \phi_k(X) = [1, (X - c_k)^T]^T. \tag{22}$$

with c_k being the center of the k-th local estimator.

Assume $D \subseteq \cup_{k=1}^N S_k$, where $S_k = \{X : w_k \neq 0\}, k = 1, 2, \cdots, N$ are a series of compact sets. Define $w_k(X)$ as follows:

$$w_k(X) = \begin{cases} (1 - (||X - c_k||/\mu_k)^2)^2, & \text{if } ||X - c_k|| \leq \mu_k \\ 0, & \text{otherwise} \end{cases} \tag{23}$$

where μ_k is the radius of S_k. Let $\bar{w}_k(X) = w_k(x)/\sum_k w_k(X)$. Then, (20) can be equivalently expressed as follows:

$$\hat{f}(X) = \sum_{k=1}^{N} \bar{w}_k \hat{f}_k(X). \tag{24}$$

Define the optimal parameter θ_k^* for $X \in S_k$ as follows:

$$\theta_k^* = \arg\min_{\theta_k} \left(\int_{X \in D} w_k(X) ||f(X) - \hat{f}_k(X)||^2 dX \right). \tag{25}$$

Also, define the error ϵ_k as follows:

$$\epsilon_k = \begin{cases} f(X) - \hat{f}_k(X), & \text{on } \bar{S}_k \\ 0, & \text{on } D - \bar{S}_k \end{cases} \tag{26}$$

and assume $|\epsilon_k| \leq \epsilon$ with ϵ as a positive constant. Then, $f(x)$ and its locally weighted NN approximation can be expressed to be

$$f = \sum_{k=1}^{N} \bar{w}_k \theta_k^{*T} \phi_k + \sum_{k=1}^{N} \bar{w}_k \epsilon_k, \tag{27}$$

$$\hat{f} = \sum_{k=1}^{N} \bar{w}_k \theta_k^T \phi_k. \tag{28}$$

It is obvious that $|\sum_{k=1}^N \bar{w}_k \epsilon_k| \leq \max(|\epsilon_k|) \sum_{k=1}^{N_i} \bar{w}_k \leq \epsilon$.

Let $\tilde{\theta}_k = \theta_k^* - \theta_k$ and $\Omega_k \triangleq \{\theta_k : ||\theta_k|| \leq c_{\theta k}\}$, and define

$$c = \max_{\theta_k^*, \theta_k \in \Omega_k} \sum_{k=1}^{N} \tilde{\theta}_k^T \tilde{\theta}_k / \eta$$

with η being a positive design parameter. Design the update law of θ_k to be

$$\dot{\theta}_k = \text{Proj}\left(\eta \bar{w}_k \phi_k \xi^T\right) \tag{29}$$

where Proj(.) is a projection operator given by

$$\text{Proj}(.) = \begin{cases} 0, & \text{if } \theta_k = -c_{\theta k} \text{ and } . < 0 \\ 0, & \text{if } \theta_k = c_{\theta k} \text{ and } . > 0 \\ ., & \text{otherwise} \end{cases} \tag{30}$$

3.3 Stability Analysis

Theorem. Consider the system (1) with constraints (3). Assume Assumptions 1–3 hold and $X(0) \in D, \tau(0) = 0$, and the control law is designed as (19). Let

$$A_{1i} = \max_{(e_{1i}, y_{di}) \in \Omega_{1i}} |\alpha_{1i}(e_{1i}, y_{di})|, \tag{31}$$

$$A_{ri} = \max_{((\bar{e}_{2i}, \bar{y}_{di})) \in \Omega_{ri}} |\tau_{ri}(\bar{e}_{2i}, \bar{y}_{di})|, \tag{32}$$

where $\bar{e}_{2i} = [e_{1i}, e_{2i}]^T$, $\bar{y}_{di} = [y_{di}, \dot{y}_{di}]^T$, and

$$\Omega_{1i} = \{[e_{1i}, y_{di}] : |e_{1i}| \leq k_{1i}, |y_{di}| \leq A_i\}, \tag{33}$$

$$\Omega_{\tau i} = \{[\bar{e}_{1i}, \bar{y}_{di}] : |e_{1i}| \leq k_{1i}, |e_{2i}| \leq k_{2i}, |y_{di}| \leq A_i, |\dot{y}_{di}| \leq Y_i\}. \tag{34}$$

If there exist $\lambda_{1i}, i = 1, \cdots, n, \lambda_2, \lambda_3$ such that

$$b_{1i} \geq k_{1i} + A_i,\ b_{2i} \geq k_{2i} + A_{1i},\ \tau_{di} \geq k_{3i} + A_{ri},\ i = 1, \cdots, n, \tag{35}$$

then the constraints (3) are satisfied and the signals in the closed-loop control system are uniformly ultimately bounded.

Proof. Consider the following Lyapunov function:

$$V = V_3 + \frac{1}{2\eta} tr\{\sum_{k=1}^{N} \tilde{\theta}_k^T \tilde{\theta}_k\} \tag{36}$$

Based on (20) and (36), one obtains

$$\begin{aligned}
\dot{V} &= -\sum_{i=1}^{n} \lambda_{1i} \frac{e_{1i}^2}{k_{1i}^2 - e_{1i}^2} - \sum_{i=1}^{n} \lambda_2 \frac{e_{2i}^2}{k_{2i}^2 - e_{2i}^2} - \sum_{i=1}^{n} \lambda_3 \frac{e_{3i}^2}{k_{3i}^2 - e_{3i}^2} - \frac{1}{2}\xi^T \xi \\
&\quad + \xi^T (\sum_{i=1}^{N} \bar{w}_k \tilde{\theta}_k^T \phi_k + \sum_{i=1}^{N} \bar{w}_k \epsilon_k) - \frac{1}{\eta} tr\{\sum_{k=1}^{N} \tilde{\theta}_k^T \dot{\hat{\theta}}_k\} \\
&= -\sum_{i=1}^{n} \lambda_{1i} \frac{e_{1i}^2}{k_{1i}^2 - e_{1i}^2} - \sum_{i=1}^{n} \lambda_2 \frac{e_{2i}^2}{k_{2i}^2 - e_{2i}^2} - \sum_{i=1}^{n} \lambda_3 \frac{e_{3i}^2}{k_{3i}^2 - e_{3i}^2} - \frac{1}{2}\xi^T \xi \\
&\quad - \frac{1}{\eta} tr\{\sum_{k=1}^{N} \tilde{\theta}_k^T (\dot{\hat{\theta}}_k - \eta \bar{w}_k \phi_k \xi^T)\} + \xi^T \sum_{i=1}^{N} \bar{w}_k \epsilon_k.
\end{aligned} \tag{37}$$

Substituting (29) into (37), one obtains

$$\dot{V} \leq -\sum_{i=1}^{n} \lambda_{1i} \frac{e_{1i}^2}{k_{1i}^2 - e_{1i}^2} - \sum_{i=1}^{n} \lambda_2 \frac{e_{2i}^2}{k_{2i}^2 - e_{2i}^2} - \sum_{i=1}^{n} \lambda_3 \frac{e_{3i}^2}{k_{3i}^2 - e_{3i}^2} + \frac{1}{2}\epsilon^2 \tag{38}$$

As $\log[k_{ji}^2/(k_{ji}^2 - e_{ji}^2)] \leq e_{ji}^2/(k_{ji}^2 - e_{ji}^2)$ for $j = 1, 2, 3$. [21], one gets

$$\dot{V} \leq -2\lambda V_3 + \frac{1}{2}\epsilon^2 \leq -2\lambda V + \beta \tag{39}$$

where $\lambda = \min\{\lambda_{1i}, i = 1, \cdots, n, \lambda_2, \lambda_3\}$ and $\beta = \lambda c + 1/2\epsilon^2$. It is concluded from (39) that V and all closed-loop signals are bounded. Then, based on the forms of BLFs $V_i, i = 1, 2, 3$ and $X(0) \in D$, one gets $|e_{1i}| \leq k_{1i}$, $|e_{2i}| \leq k_{2i}$ and $|e_{3i}| \leq k_{3i}$. Since (35) holds, one concludes $|q_{1i}| \leq b_{1i}$, $|q_{2i}| \leq b_{2i}$ and $|\tau_i| \leq \tau_{di}$. According to (39), one also obtains

$$V(t) \leq \exp(-\lambda t)(V(0) - \frac{\beta}{2\lambda}) + \frac{\beta}{2\lambda}. \tag{40}$$

Since $\log \frac{k_{1i}^2}{k_{1i}^2 - e_{1i}^2} \leq 2V(t)$ for $i = 1, \cdots, n$, one gets

$$\log \frac{k_{1i}^2}{k_{1i}^2 - e_{1i}^2} \leq 2\exp(-\lambda t)(V(0) - \frac{\beta}{2\lambda}) + \frac{\beta}{\lambda} \tag{41}$$

from which one obtains

$$\limsup_{t\to\infty} \frac{k_{1i}^2}{k_{1i}^2 - e_{1i}^2} \leq \exp(\beta/\lambda), \tag{42}$$

$$\limsup_{t\to\infty} |e_{1i}| \leq k_{1i}\sqrt{1 - \exp(\beta/\lambda)}. \tag{43}$$

4 Simulation Results

To illustrate the effectiveness of the proposed BLFs-based locally weighted learning control law, simulations are carried out for a one-link robot manipulator with the reference trajectory $y_d = 0.5\cos(0.2t)$. The dynamics of the manipulator is given by

$$ml^2\ddot{q} + d\dot{q} + 0.5mgl\cos(q) = \tau, \tag{44}$$

where $m = 1\,\mathrm{kg}$, $l = 1\,\mathrm{m}$, $\mathrm{g} = 9.8\,\mathrm{m/s}^2$, and $d = 1\,\mathrm{kg.m}^2/\mathrm{s}$. The constraints are $|q_1| \leq 1, |q_2| \leq 1$ and $|\tau| \leq 10$ with $q_1 = q, q_2 = \dot{q}$. In the simulation, the initial system states are $q_1(0) = 0.2, q_2(0) = 0.2$.

The control is designed as

$$\tau = -7\int_0^t e_3 d\sigma - \int_0^t \frac{9^2 - e_3^2}{0.6^2 - e_2^2} e_2 d\sigma + \tau_r \tag{45}$$

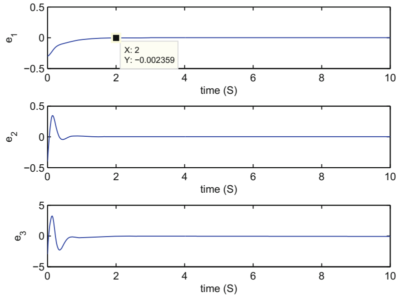
where $e_1 = q_1 - y_d, e_2 = q_2 - \alpha_1, e_3 = \tau - \tau_r$ and are constrained in $|e_1| \leq 0.5$, $|e_2| \leq 0.6$ and $|e_3| \leq 7$, and the virtual control α_1, τ_r are described by

$$\tau_r = -5e_2 + \dot{\alpha}_1 - \hat{f} - 0.5\frac{e_2}{0.6^2 - z_2^2} - \frac{0.6^2 - e_2^2}{0.5^2 - e_1^2}e_1$$
$$\alpha_1 = -2e_1 + \dot{y}_d$$

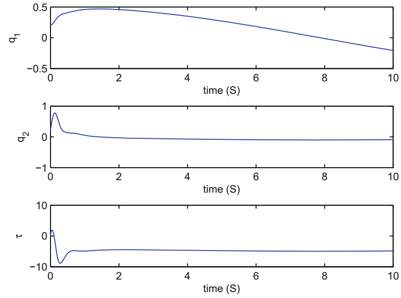
where $\hat{f}$ is a localized adaptive NN approximation of $f = -q_2 + 9.8/2\cos(q_1)$. In the NN approximation, the centers location are chosen as $c_1 = [-1, 1]^T$,

$c_2 = [0,1]^T, c_3 = [1,1]^T, c_4 = [-1,0]^T, c_5 = [0,0]^T, c_6 = [1,0]^T, c_7 = [-1,-1]^T, c_8 = [0,-1]^T, c_9 = [1,-1]^T, c_{10} = [-0.5,0.5]^T, c_{11} = [0.5,0.5]^T, c_{12} = [-0.5,-0.5]^T$, $c_{13} = [0.5,-0.5]^T$, $c_{\theta k} = 0.5$, $\eta = 100$, $\mu_k = 1.5$, and the basis functions are chosen as $\phi_i = [1, q_1, q_2]^T - [0; c_i], i = 1, \cdots, 13$.

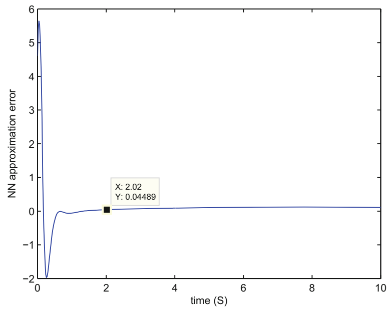
Simulation results are presented in Fig. 1(a)–(c), where Fig. 1(a) shows the tracking errors e_1, e_2 and e_3, Fig. 1(b) shows the performance of the states q_1, q_2 and the control input τ, and Fig. 1(c) shows the NN approximation error $f - \hat{f}$. From Fig. 1(a), the tracking error is near to 0 after 2 s and the constraints satisfaction $|e_1| \leq 0.5, |e_2| \leq 0.6, |e_3| \leq 7$ and $|q_1| \leq 1, |q_2| \leq 1, |\tau| \leq 10$ is easily seen from Fig. 1(a)–(b). From Fig. 1(c), one sees that the approximation error $f - \hat{f}$ converges to a small neighborhood of zero after 2 s. Therefore, the designed adaptive NN control law makes the system state and control input constraints fulfilled and the tracking error converge to a small neighborhood of 0.



(a)



(b)



(c)

Fig. 1. Control trajectories by the proposed controller. (a) The tracking errors e_1, e_2 and e_3. (b) The states q_1, q_2 and control input τ. (c) The NN approximation error $f - \hat{f}$.

5 Conclusions

A BLFs-based adaptive NN control law was designed for robot manipulators with position, velocity and control constraints. The uncertainties were approximated by locally weighted adaptive NNs and the system constraints were tackled by using BLFs in the backstepping procedure. The control feasibility and uniform boundedness of all closed-loop signals were verified by theoretical analysis. From simulation results, we can see that under the proposed control the system constraints were never violated and absolute value of the tracking error converged to a small neighborhood of zero.

Acknowledgments. This work was supported by the National Natural Science Foundation of China under Grant No. 61503158, the MoE Tier 1 Grant from the Ministry of Education, Singapore, under WBS R-397-000-218-112, and the Priority Academic Program Development of Jiangsu Higher Education Institutions.

References

1. Huh, S.H., Bien, Z.: Robust sliding mode control of a robot manipulator based on variable structure-model reference adaptive control approach. IET Control Theory Appl. **1**(5), 1355–1363 (2007)
2. Islam, S., Liu, X.P.: Robust sliding mode control for robot manipulators. IEEE Trans. Ind. Electron. **58**(6), 2444–2453 (2011)
3. Sun, T., Pei, H., Pan, Y., Zhou, H., Zhang, C.: Neural network-based sliding mode adaptive control for robot manipulators. Neurocomputing **74**(14), 2377–2384 (2011)
4. Sun, T., Pei, H., Pan, Y., Zhang, C.: Robust adaptive neural network control for environmental boundary tracking by mobile robots. Int. J. Robust Nonlinear Control **23**(2), 123–136 (2013)
5. Chen, L., Hou, Z.G., Tan, M.: Adaptive neural network tracking control for manipulators with uncertain kinematics, dynamics and actuator model. Automatica **45**(10), 2312–2318 (2009)
6. Li, T., Duan, S., Liu, J., Wang, L., Huang, T.: A spintronic memristor-based neural network with radial basis function for robotic manipulator control implementation. IEEE Trans. Syst. Man Cybern.: Syst. **46**(4), 582–588 (2016)
7. Pan, Y., Liu, Y., Xu, B., Yu, H.: Hybrid feedback feedforward: an efficient design of adaptive neural network control. Neural Netw. **76**, 122–134 (2016)
8. Patino, H.D., Carelli, R., Kuchen, B.R.: Neural networks for advanced control of robot manipulators. IEEE Trans. Neural Netw. **13**(2), 343–354 (2002)
9. Wai, R.J., Muthusamy, R.: Design of fuzzy-neural-network-inherited backstepping control for robot manipulator including actuator dynamics. IEEE Trans. Fuzzy Syst. **22**(4), 709–722 (2014)
10. Wai, R.J., Chen, P.C.: Intelligent tracking control for robot manipulator including actuator dynamics via TSK-type fuzzy neural network. IEEE Trans. Fuzzy Syst. **12**(4), 552–560 (2004)
11. Seo, D.: Adaptive control for robot manipulator with guaranteed transient performance. In: IEEE Conference on Decision and Control, pp. 2109–2114 (2016)

12. Ngo, K.B., Mahony, R.: Bounded torque control for robot manipulators subject to joint velocity constraints. In: IEEE International Conference on Robotics and Automation, pp. 7–12 (2006)
13. Papageorgiou, X., Kyriakopoulos, K.J.: Motion tasks for robot manipulators subject to joint velocity constraints. In: IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 2139–2144 (2008)
14. Zhang, Z., Zhang, Y.: Variable joint-velocity limits of redundant robot manipulators handled by quadratic programming. IEEE/ASME Trans. Mechatron. **18**(2), 674–686 (2013)
15. Zhang, Y., Ge, S.S., Lee, T.H.: A unified quadratic-programming-based dynamical system approach to joint torque optimization of physically constrained redundant manipulators. IEEE Trans. Syst. Man Cybern. B Cybern. **34**(5), 2126–2132 (2004)
16. Subudhi, B., Pradhan, S.K.: Direct adaptive control of a flexible robot using reinforcement learning. In: 2010 International Conference on Industrial Electronics, Control & Robotics, pp. 27–29 (2010)
17. He, W., Chen, Y., Yin, Z.: Adaptive neural network control of an uncertain robot with full-state constraints. IEEE Trans. Cybern. **46**, 620–629 (2016)
18. He, W., David, A.O., Yin, Z., Sun, C.: Neural network control of a robotic manipulator with input deadzone and output constraint. IEEE Trans. Syst. Man Cybern. Part A-Syst. **46**(6), 759–770 (2016)
19. Kwan, C., Lewis, F.L.: Robust backstepping control of nonlinear systems using neural networks. IEEE Trans. Syst. Man Cybern. Part A-Syst. **30**(6), 753–766 (2000)
20. Kuljaca, O., Swamy, N., Lewis, F.L., Kwan, C.: Design and implementation of industrial neural network controller using backstepping. IEEE Trans. Ind. Electron. **50**(1), 193–201 (2003)
21. Liu, Y.J., Li, J., Tong, S.C., Philip Chen, C.L.: Neural nework control-based adaptive learning design for nonlinear systems with full-state constraints. IEEE Trans. Neural Netw. Learn. Syst. **27**(7), 1562–1570 (2016)